

Statistical Approach for MRI Brain Tumor Quantification

N. S. Zulpe

Lecturer

Department of Computer Sci.,
COCSIT, Latur, India,

S. S. Chowhan

Lecturer

Department of Computer Sci.,
COCSIT, Latur, India,

Dr. V. P. Pawar

Associate Prof.

Department of Computer Sci.,
SRTMU, Nanded, India,

ABSTRACT

Human anatomy obtained by different modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Position Emission Tomography (PET), etc. Brain tumor diagnosis is easy by using these medical equipments. The physician needs the correct measurement of the tumor area for the further treatment, this need to extract the abnormal part from the 2D MRI scan accurately and measure the region of interest and Human-Computer interaction is helpful for this procedure. We have used disease affected MRI scans from the Whole Brain Atlas (WBA) for the experiment. In this paper, we have presented a semiautomatic segmentation method to extract the tumor from MRI scan and measure the exact area of the brain tumor by using statistical approach.

Keywords

MRI, PET, CT, WBA, Human-computer Interaction.

1. INTRODUCTION

The arrival of medical imaging sources such as Computed tomography (CT), Positron emission tomography (PET) and magnetic resonance imaging (MRI) has improved the diagnosis of various diseases of human being. Segmentation is the partitioning of an image into meaningful regions, most frequently to distinguish objects or regions of interest (“foreground”) from everything else (“background”). In the simplest cases, there would be only these two classes (foreground and background) and the segmented image would be binary image. The medical image segmentation is one of the difficult tasks in the image processing and segmentation of ROI may give accurate measurement or inaccurate measurement [1].

In the brain MR image, the tumor is shown clearly. For the treatment, the physician also needs the quantification of the tumor area. This requires the abnormal part in the image to be segmented accurately; afterward the segmented area is measured. The computer can give great help during this procedure. Chunyan Jiang et. al. introduced one system to perform the task mentioned above. In this system, the brain tumor MR image is segmented semi-automatically. One deformable model-based method is adapted in their system [2]. Liu et al. have proposed a method for brain tumor segmentation and tumor volume measurement, which is based on the fuzzy-connectedness theory and requires a prior knowledge of the estimated location of the tumor [3]. Anthony Yezzi et.al. employed the new geometric active contour models for edge detection and segmentation of magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound medical imagery. The model is based on defining feature-based metrics on a given image, which in

turn leads to a novel snake paradigm in which the feature of interest may be considered to lie at the bottom of a potential well [4]. Mrs.Mamata S.Kalas developed an automated cancer recognition system for MRI images. she implemented the neuro fuzzy logic for the classification and estimation of cancer affect on given MRI image [5].

T.Logeswari and M.Karnan has used a clustering based approach using a Self Organizing Map (SOM). Their algorithm is proposed for medical image segmentation. They described segmentation method consists of two phases. In the first phase, the MRI brain image is acquired from patient database. In that film artifact and noise are removed. In the second phase MR image segmentation, accurately identify the principal tissue structures in these image volumes. A new unsupervised MR image segmentation method based on fuzzy C-Means clustering algorithm for the Segmentation is presented [6].

Thresholding technique can be used for MRI brain tumor segmentation. According to intensity/brightness is a simple technique for images which contain solid objects on a background of different, but uniform, brightness. Each pixel is compared to the threshold: if its value is higher than the threshold, the pixel is considered to be “foreground” and is set to white, and if it is less than or equal to the threshold it is considered “background” and set to black [1]. Various versions of thresholding technique have been introduced that segments MR images by using the information based on local intensities and connectivity [7]. Though this is a simple technique, still there are some factors that can complicate the thresholding operation, for example, nonstationary and correlated noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast, and object size not commensurate with the scene [9]. Chowdhury et.al. introduced a new image thresholding method based on the divergence function. In this method, the objective function is constructed using the divergence function between the classes, the object and the background. The required threshold is found where this divergence function shows a global minimum [10]. In contour-based methods, Lefohn et al. have proposed a semi-automatic method for tumor segmentation using level sets. The user selects the tumor region, to initialize a first segmentation. Based on a visual inspection of the results, he tunes the level set parameters and the segmentation process is repeated [11]. S. Ho et.al. associate level set evolution with region competition. Their algorithm uses two images (T1-weighted with and without contrast agents) and calculates a tumor probability map using classification, histogram analysis and the difference between the two images, and then this map is used as the zero level of the level set evolution [12]. The semi-automatic method based on level sets was proposed by K. Xie et.al. In this approach, the user

selects a ROI and then a level set method is applied to segment the tumor [13].

1.1 MAGNETIC RESONANCE IMAGING

A magnetic resonance imaging instrument (MRI Scanner) uses powerful magnets to polarize and excite hydrogen nuclei i.e. proton in water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body. MRI uses three electromagnetic fields

- I) A very strong static magnetic field to polarize the hydrogen nuclei, called the static field.
- II) A weaker time varying field(s) for spatial encoding called the gradient field.
- III) A weak radio frequency field for manipulation of hydrogen nuclei to produce measurable signals collected through RF antenna. The brain can be viewed from three directions as depicted in figure 1.

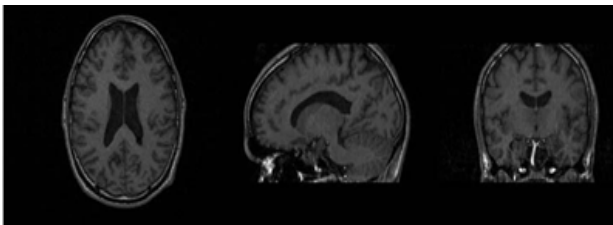


Fig 1: a) Transaxial View b) Sagittal View c) Coronal View

2. METHODS AND MATERIALS

2.1 MR Images

The source for the MR images is Whole Brain Atlases (WBA) from where we have collected all T1-weighted MRI images with dimension of each image was 256 x 256 pixels. WBA gives us normal as well as abnormal MR brain scans and for the experiment, we use different classes of databases such as:

- i) Gliomas class- Slow growing, with relatively well-defined borders.
- ii) Astrocytoma- Slow growing, Rarely spreads to other parts of the CNS, Borders not well defined.
- iii) Anaplastic Astrocytoma Grows faster.
- iv) Glioblastoma multiforme (GBM) Most invasive type of tumor, Commonly spreads to nearby tissue, Grows rapidly [5].

Four different slices of 1mm thickness showing the Glioma brain tumor is used for the actual experimental work.

2.2 Median Filter

The *median filter* is an effective method that can suppress isolated noise without blurring sharp edges. Specifically, the median filter replaces a pixel by the median of all pixels in the neighborhood:

$$y[m,n] = median\{x[i,j], (i,j) \in w\} \tag{1.1}$$

where w represents a neighborhood centered around location (m,n) in the image. On collected tumor affected MR image at first, we applied the Median filter to remove the noise from the given image. Neighborhood averaging can suppress

isolated out-of-range noise, but the side effect is that it also blurs sudden changes (corresponding to high spatial frequencies) such as sharp edges.

2.3 Binarization

Image binarization converts an image of up to 256 gray levels to a black and white image. Binarization is used as a pre-processor before OCR. In fact, most OCR packages on the market work only on bi-level (black & white) images. The simplest way to use image binarization is to choose a threshold value, and classify all pixels with values above this threshold as white, and all other pixels as black. The problem then is how to select the correct threshold. In many cases, finding one threshold compatible to the entire image is very difficult, and in many cases even impossible. Therefore, adaptive image binarization is needed where an optimal threshold is chosen for each image area.

- For the equalized image the pixels are represented in a 0 to 255 gray level intensity.
- As the process is to extract the affected region or the accumulated region, a 2-level image representation would be sufficient for better computation.
- For the binarization of equalized image a thresholding method is used as illustrated :
- Binarized Image $b_{i,j} = 255$ if $e(i,j) > T$ else $b_{i,j} = 0$ where $e(i,j)$ is the equalized MRI image and T is threshold derived for the equalized image.
- M is the masking matrix derived using neighbor-hood estimation method, as given :

$$\text{Let } e = \begin{matrix} p1 & p2 & p3 \\ p4 & p5 & p6 \\ p7 & p8 & p9 \end{matrix}$$

be the equalized image matrix. Then the masking element

$$M(p5) = \max(|p4 - p6|, |p2 - p8|) \tag{1.2}$$

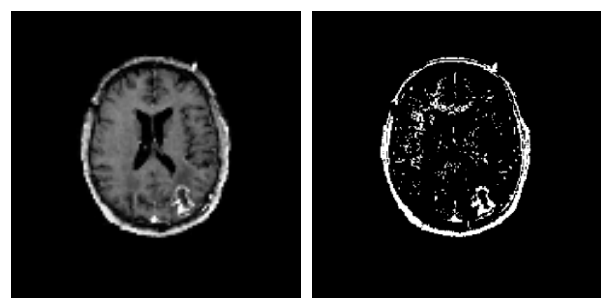


Fig 2: (a) Original Image (b) Binarized image

2.4 Semiautomatic segmentation:

We want to segment Tumor affected part i.e. region of interest (ROI) from the given disease affected MR image. We have defined ROI by creating a binary mask that is a binary image with pixels that define ROI set to 1 and all other pixels set to 0. By using human computer interaction we have created this binary mask and extracted the tumor affected part from the given MRI image.

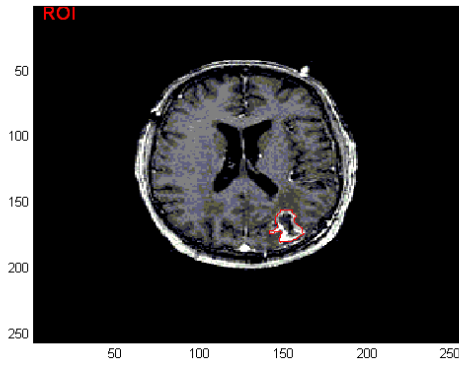


Fig 3: ROI in MRI scan

2.5 Histogram of an ROI

The histogram of a digital image with L total possible intensity levels in the range $[0, G]$ is defined as the discrete function $h(r_k) = n_k$ where r_k is the k^{th} intensity level in the interval $[0, G]$ and n_k is the number of pixels in the image whose intensity level is r_k , we found the histogram of the region of interest (ROI) which is helpful to find out the number of pixels in that area.

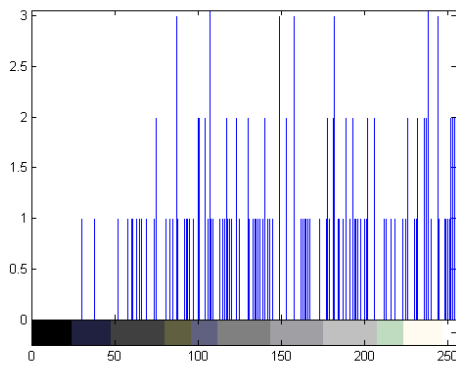


Fig 4: Histogram of ROI

2.6 Statistical Approach

1×2 vector ; the center of mass of the region. The first element of centroid is the horizontal coordinate (or x-coordinate) of the center of mass, and the second element is the vertical coordinate (or y-coordinate)

Mean: A measure of average intensity

$$m = \sum_{i=0}^{L-1} z_i p(z_i) \quad (1.3)$$

Where z_i is a random variable indicating intensity, $p(z)$ is the histogram of the intensity levels in a region, L is the number of possible intensity levels, m is the mean (average) intensity.

Standard Deviation: A Measure of average contrast

$$\sigma = \sqrt{\mu_2(z)} = \sqrt{\sigma^2} \quad (1.4)$$

Where $\mu_2(z)$ is the second moment (variance) σ^2

Entropy: A Measure randomness

In an image, the pixel values, a_i , occur with probabilities $P(a_i)$, which are given by the bin heights of the normalized

histogram; the available pixel values run from 0 to $2^n - 1$. First-order statistics assume that the statistical properties of the pixels do not depend on neighboring pixels. A first-order estimate of the entropy, H , of an image is given by the sum of the information content of each pixel:

$$H = - \sum_{i=0}^{2^n-1} p(a_i) I(a_i) \quad (1.5)$$

EquiDiameter: specifies the diameter of a circle with the same area as the region. Computed as $\sqrt{4 * \text{Area} / \pi}$.

Eccentricity: specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1 .

Perimeter: p -element vector containing the distance around the boundary of each contiguous region in the image, where p is the number of regions. 'regionprops' computes the perimeter by calculating the distance between each adjoining pair of pixels around the border of the region.

3. RESULTS

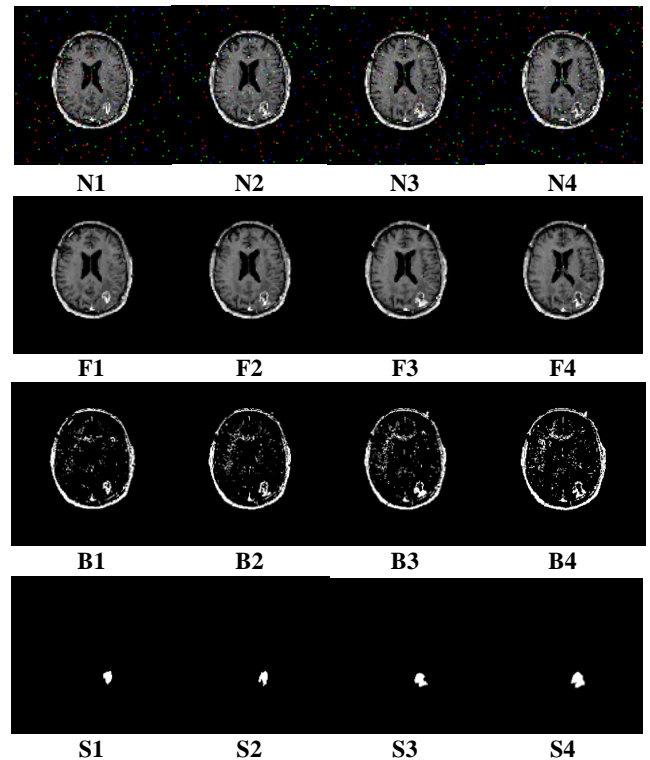


Fig 5: Noisy Images (N1,N2,N3,N4),Filtered Images(F1,F2,F3,F4), Segmented Images(S1,S2,S3,S4)

Table 1: Measurement of Area, S, M.

Segmented Images	No. of Pixels Area/(mm ³)	Standard Deviation (S)	Mean (M)
Tumor Segmented Image (s1)	238/(6.29)	0.0529	0.0028
Tumor Segmented Image (s2)	273/(7.22)	0.0571	0.0033
Tumor Segmented Image (s3)	325/(8.59)	0.0602	0.0036
Tumor Segmented Image (s4)	353/(9.33)	0.0650	0.0042

Table 2: Measurement of centroid and entropy.

Segmented Images	Centroid of Tumor Area		Entropy
	X	Y	E
Tumor Segmented Image (s1)	151.3311	164.0135	6.4138
Tumor Segmented Image (s2)	149.7123	165.3302	6.7636
Tumor Segmented Image (s3)	151.3994	168.2492	6.8807
Tumor Segmented Image (s4)	152.0855	167.5074	7.0437

Table 3: Measurement of perimeter, equidiameter and eccentricity

Segmented Images	Perimeter (p)	Equidiameter (e)	Eccentricity (e)
Tumor Segmented Image (s1)	60.8701	15.3476	0.8159
Tumor Segmented Image (s2)	75.6985	16.6985	0.6771
Tumor Segmented Image (s3)	84.7696	20.5291	0.7136
Tumor Segmented Image (s4)	94.0833	20.5600	0.6901

4. CONCLUSION

In this paper we have used median filter on the Glioma brain tumor MR image to remove the noise. Then binary mask is applied over the given MR images and with the help of human-computer interaction segment the abnormal part from the given MRI scan. On the ROI we applied some statistical function to find out the average intensity, average contrast and calculated the some of the region properties which is helpful for the accurate measurement of the tumor part. We have used only semiautomatic segmentation technique in which user needs to give the initial seed contour for the segmentation. In the future work we will work on every class of the tumor and try to provide the fully automatic segmentation technique to find out the region of interest (ROI).

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